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Location Matters: An Examination of Trading Profits

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ABSTRACT

The electronic trading system Xetra of the German Security Exchange provides a unique data source on the equity trades of 756 professional traders located in 23 different cities and eight European countries. We explore informational asymmetries across the trader population: Traders located outside Germany in non-German-speaking cities show lower proprietary trading profit. Their underperformance is not only statistically significant, it is also of economically significant magnitude and occurs for the 11 largest German blue-chip stocks. We also examine whether a trader location in Frankfurt as the financial center, or local proximity of the trader to the corporate headquarters of the traded stock, or affiliation with a large financial institution results in superior trading performance. The data provide no evidence for a financial center advantage or of increasing institutional scale economies in proprietary trading. However, we find evidence for an information advantage due to corporate headquarters proximity for high-frequency (intraday) trading.

INFORMATION AND ITS PRESUMED ASYMMETRIC distribution has become an important aspect of financial market theory. Yet even though information heterogeneity of agents is now a common assumption in microstructure models, direct evidence for the scope of such asymmetry is hard to provide.[1] Existing theories offer little guidance as to who should be the better-informed investors. Moreover, it has proven difficult to document the existence of any investor group that consistently outperforms the market. For example, professional mutual fund managers appear unable to "beat" the market.[2]

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[1] Direct evidence for asymmetric information is provided by court cases on insider trading. But this gives little insight with respect to the scope of information asymmetries in the outsider population.

[2] See, for example, Chevalier and Ellison (1999) and Malkiel (1995).

This paper uses geographic trader locations as proxies for information asymmetry. We examine the proprietary trading profits of 756 professional traders located in eight European countries with equal access to Xetra—the electronic trading platform of the German Security Exchange. The nondiscriminatory nature of the trading system means that our data are particularly well suited for assessing the scope of international information barriers in equity trading. The most important result of our analysis is that foreign traders in non-German-speaking financial centers have inferior trading profits in their proprietary trading of German stocks. Their relative trading losses are most pronounced for medium-frequency (intraweek) and low-frequency (intraquarter) trading. Foreign underperformance is not only statistically significant, it is also of economically significant magnitude and occurs for large blue-chip stocks.

The literature on portfolio allocation has given increasing emphasis to the role of international information asymmetry. Gehrig (1993), Brennan and Cao (1997), and Kang and Stulz (1997) all emphasize informational asymmetry as their preferred explanation for the concentration of portfolio investment in domestic assets known as the "home equity bias."[3] It is argued that linguistic and cultural borders often coincide with international borders and represent formidable information barriers. Kang and Stulz document that foreign investment in Japanese equity is concentrated in large and export-oriented firms for which the international information asymmetry is presumably smaller. Coval and Moskowitz (1999a) show that even U.S. domestic portfolio funds are geographically biased toward the home of the fund, which suggests that information asymmetry may have a strictly geographic dimension. Asset proximity can then provide an information advantage even in the absence of cultural and linguistic information barriers. Grinblatt and Keloharju (1999) confirm the intracountry geographic investment bias for Finnish data. But they also identify a separate language bias in the investment behavior of the Swedish-language minority. Evidence about asset flows also assigns a role to geography. Portes and Rey (1999) are able to explain a large proportion of global equity flows using a gravity model in which distance is interpreted as a proxy for information costs.

Common to all these contributions is that information asymmetry is indirectly inferred from asset allocation decisions. But such allocation decisions may reflect investment preference of a purely psychological nature. To learn more about information asymmetry, we must look directly at investment profitability. Coval and Moskowitz (1999b) examine the regional investment bias of U.S. mutual funds and find that their local investment generates a

[3] Initial explanations focused on barriers to international investment such as government restrictions on foreign and domestic capital flows, foreign taxes, and variable transaction costs like transaction tariffs and fees. Tesar and Werner (1995) argue against such variable transaction costs, which should decrease asset turnover; they find evidence that foreign portfolio turnover exceeds the turnover of domestic equity. For a recent overview on the home equity bias, see Lewis (1999).

higher average return. International evidence is provided by Shukla and van Inwegen (1995), based on U.S. and U.K. mutual funds. Controlling for differential tax treatment and for fund expenses and objectives, they find that U.K. fund managers investing in the United States underperform relative to their U.S. colleagues. Bacidore and Sofianos (2000) use inventory data on NYSE specialists to document higher information asymmetry and increased adverse selection risk for their market making in non-U.S. stocks relative to U.S. stocks. Other evidence runs against a simple story of a foreign information disadvantage. Grinblatt and Keloharju (2000) calculate profit measures based on daily positions in large Finnish stocks registered by the depository institution. They find that foreign investors outperform the investments of Finnish households and interpret this as evidence for higher financial sophistication of the foreign investor group. Similarly, Seasholes (2000) finds information advantages for foreign capital flows into Taiwan and Thailand. However, it is difficult to exclude the possibility that domestic investors use offshore capital in their domestic investment.

Our paper looks at international information asymmetry as revealed by the proprietary trading profits of professional traders. For professional traders, we can assume a high and similar degree of financial sophistication. Moreover, they use the same trading system in a similar European time zone. Most important, the location of the investment decision maker is clearly identified. We calculate trading profits based on actual transaction data over a four-month period. This is a rather short time span relative to the long-run data available for mutual funds, but transaction data do present a number of advantages over mutual fund data. First, we can assure data completeness. We do not have any self-selection or survivorship problems, since our data set includes all transactions of all traders participating in the electronic limit order book.[4] Second, the data allows us to calculate market-to-market trading profits exclusive of fees and transaction costs. Third, we can compare the cross-sectional investment behavior of different investors in the same asset. Transaction data thus avoids the difficult problem of comparing investment strategies with different unknown risk profiles based on beta or other factors.

The empirical work is organized around five key hypotheses concerning the information geography of a stock market.

H1. *Financial center hypothesis:* Traders located in the German financial center (Frankfurt) enjoy an information advantage over other traders for trading in German equity. Local interaction between traders and financial intermediaries, mostly situated in Frankfurt, improves trading performance.

[4] By contrast, the survivorship bias in mutual fund data is likely to vary across different national fund samples. For a discussion of the selection bias in U.S. mutual fund data, see Malkiel (1995).

H2. *Joint cultural and geographic distance hypothesis*: Traders outside Germany in non-German-speaking locations face an information disadvantage and trade less profitably. The information barrier may be either linguistic or geographic in nature.[5]

H3. *Pure geographic distance hypothesis*: Traders outside Germany in the German-speaking financial centers of Austria and Switzerland have less information because of geographic distance. We assume that linguistic or cultural information barriers do not matter for Austria and Switzerland.

H4. *Headquarters proximity hypothesis*: Traders located in local proximity to the corporate headquarters of the traded corporation enjoy a comparative information advantage and show superior trading performance in the "local stock." The information advantage results from local interaction with headquarters staff that is facilitated by geographic proximity.

H5. *Institutional economies of scale hypothesis*: Traders in large financial institutions with many traders enjoy an information advantage over those in smaller institutions. First, traders in large institutions may have access to better information sources like databases or in-house research. Second, they may enjoy private information about a larger client order flow.

The remainder of the paper is organized as follows. Section I discusses the institutional framework and the data. The methodology for calculating trading profits is explained in Section II. To distinguish the profitability of market making at intraday, intraweek, and intraquarter frequencies, we undertake a spectral profit decomposition inspired by Hasbrouck and Sofianos (1993). In the Appendix we provide further details on the technical aspects of such a decomposition. The dependent variables are explained in Section III, and the regression results are discussed in Section IV. Section V summarizes the results and concludes.

I. Institutional Framework and Data

In June 1997, the German Security Exchange introduced an order-driven electronic trading platform named Xetra. Since that time, the Xetra system has covered an increasing percentage of German security trading. It allows decentralized and equal access to the German stock market. By October 1998, approximately 1,600 stocks could be traded via more than 1,300 trading

[5] A financial institution in a non-German-speaking country could employ a German-speaking trader to eliminate linguistic information barriers. We are not able to verify the distribution of German language skills, but assume here that it is on average lower in the foreign trader community.

terminals in 11 countries. This wide distribution of trader locations makes Xetra a most suitable system for testing the microstructure hypothesis of an asymmetric information geography in equity trading.

The Xetra system supports continuous electronic trading through an open limit order book. The trader identity remains anonymous in the order book. Both the beginning and the end of the trading day are marked by an auction in each security. Additional intraday auctions can be triggered by large price movements. The system executes trades based on strict price and time priority.[6]

Our data set on Xetra transactions comes from the Trading Surveillance Unit of the Frankfurt Securities Exchange. It contains all electronic Xetra trades for the 11 German blue-chip stocks represented in the Stoxx 50 index over the four-month period August 31, 1998 to December 31, 1998. Figure 1 plots the price history for the 11 stocks. The trading platform Xetra accounted for more than 90 percent of the turnover in the German blue chips.[7] Parallel floor transactions or transactions in other exchanges with cross-listings are not part of the data set. The transaction data include transaction time, price, volume, and an identification number for each of the two traders; we also know the time of the order placement (as opposed to order execution). This enables us to identify which counterpart initiated the trade.[8] Furthermore, Xetra trades distinguish proprietary trading (own-account) from client trading (agent). This distinction allows us to reconstruct the proprietary trading history for each trader.

An additional advantage of our data set is that we can infer the trader location. The data indicate the institutional affiliation of each trader as a partially encrypted five-letter code. The last two letters (non-encrypted) of this code indicate the location (e.g., xxxFR for Frankfurt).[9] The first three letters of the institutional code are encrypted to prevent identification of any particular institution. The institutional code is part of our data set but is not revealed by the order book. The identification of the trader location based on institutional code might be incorrect for those institutions that operate trading

[6] A detailed documentation of the Xetra trading system is available online at http://www.exchange.de. See, in particular, DB (1998).

[7] Only Daimler-Chrysler (DCX) and Deutsche Telecom (DTE) have a significant trading volume (about 20 percent) outside Xetra owing to cross-listings at the NYSE. Our results are not sensitive to the exclusion of these two stocks.

[8] We refer to trade-initiating orders (executed against existing limit orders in the order book) as market orders, even though those orders may formally have a limit price attached to them. The strict time preference of the execution mechanism implies that the limit price of the first-placed limit order determines the transaction price. The second limit order works like a market order.

[9] We used a public list of Xetra members (DB (1999)) to verify that the institutional code correctly indicates the trader location. The member list states the institutional code as well as the name and telephone number of the head trader. We checked the institutional code against the area code of the trader's telephone number. We found only two errors for the 335 listed members: Bankers Trust International PLC (brtFR) and Credit Agricole Indosuez Cheuvreux Deutschland GmbH (chvFR) indicate a Frankfurt location even though their head traders are listed with telephone numbers in London and Paris, respectively.

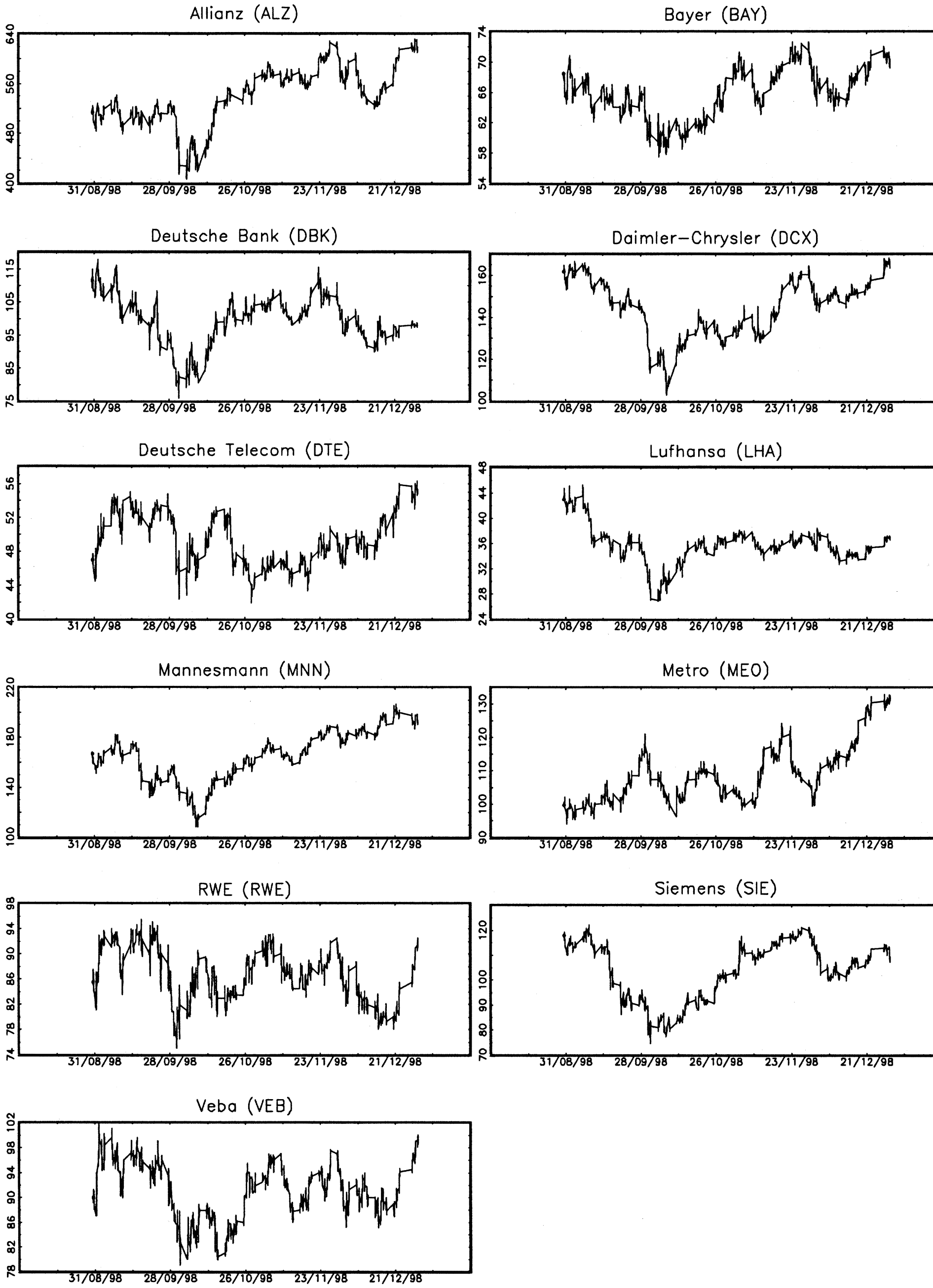

Figure 1. The price history of 11 German blue-chip stocks in the Stoxx 50 index over the 4-month period August 31, 1998 to December 31, 1998. These stocks are Allianz (ALV), Bayer (BAY), Deutsche Bank (DBK), Daimler-Chrysler (DCX), Deutsche Telecom (DTE), Lufthansa (LHA), Mannesmann (MNN), Metro (MEO), RWE (RWE), Siemens (SIE), and Veba (VEB).

Table I

Trader Population

Summary statistics for the number of traders and their combined trades for 11 German stocks in the Stoxx 50 index for the period August 31, 1998 to December 31, 1998. Proprietary traders trade on their own account, and sample proprietary traders undertake at least 10 proprietary trades in the respective stock. The 11 German stocks in the Stoxx 50 index are Allianz (ALV), Bayer (BAY), Deutsche Bank (DBK), Daimler-Chrysler (DCX), Deutsche Telecom (DTE), Lufthansa (LHA), Mannesmann (MNN), Metro (MEO), RWE (RWE), Siemens (SIE), and Veba (VEB).

	All Traders		Proprietary Traders		Sample Prop. Traders	
Stock	Number	Trades	Numbers	Trades	Number	Trades
ALV	930	116,984	540	74,736	374	74,112
BAY	995	119,472	569	70,028	414	69,404
DBK	1,102	198,050	653	130,827	499	130,180
DCX	1,126	223,954	669	132,212	515	131,574
DTE	925	125,508	546	77,626	405	77,082
LHA	920	90,190	498	49,158	326	48,470
MEO	870	82,526	487	48,811	326	48,183
MNN	947	139,132	542	85,801	395	85,137
RWE	817	68,228	467	43,143	285	42,358
SIE	1,012	150,480	589	96,676	428	96,066
VEB	927	95,888	532	59,906	359	59,147
Total	1,342	1,410,412	883	868,924	756	861,713

terminals in more than one location; this is the case for only 9 of 335 institutions.[10] For these members, the code typically indicates Frankfurt as the trading location even if it is undertaken from a terminal in London or Paris.

In order to have a sufficient number of trading events for each trader in each stock, we restrict our sample to traders who undertake at least 10 proprietary transactions in at least one stock. If a trader undertakes fewer than 10 proprietary transactions in a particular stock, then we exclude those transactions from our analysis. This reduces the original sample of 1,342 traders in 11 countries to 756 traders in 8 countries.[11] Table I provides summary statistics for the number of traders and their combined transactions for each of the following three groups: (i) all traders, (ii) proprietary traders,

[10] The document "Xetra members" (DB (1999)) lists these nine institutions separately.

[11] In a previous version of the paper, we set a much higher threshold value of 100 transactions for each account; this reduces the number of profit observation to 1,653 for 451 large traders. The higher threshold increases the average quality of the profit observations (since more trades enter on average) at the cost of reducing the cross-sectional sample size. In particular, it reduces the number of profit observations for Austrian and Swiss traders to a very small number. The main results of our paper are robust with respect to this trade-off. We also verify that the excluded proprietary transactions do not generate any selection bias for the profit statistics of the different geographic trader groups.

and (iii) sample proprietary traders with at least 10 stock transactions in a single stock. For all 11 blue-chip stocks, proprietary transactions account for 61.6 percent of the Xetra transactions. Our sample (with the cut-off at 10 trades) covers 99.2 percent of all proprietary trades. The remainder of the paper focuses on this subset of trades.

II. Methodology

In this section, we explain the methodology and the econometric model specification. Let $s = 1, 2, \ldots, T$ denote the sequence of market transactions in a particular stock, and let q_s denote the (signed) inventory change (transaction quantity) for a particular trader. We define the inventory position $\tilde{Q}_t$ of the trader as the deviation of the accumulated quantity $Q_t = \sum_{s=1}^{t} q_s$ from its long-run average inventory level $\bar{Q} = (1/T)\sum_{t=1}^{T} Q_t$. Formally, $\tilde{Q}_t = Q_t - \bar{Q}$. The average inventory $\bar{Q}$ is estimated from the data because we do not have any information about the initial inventory level at the beginning of the sample period.[12]

The price change following transaction s is given by $\Delta P_{s+1} = P_{s+1} - P_s$. The market-to-market profit over a period of T market transactions is calculated as $\sum_{s=1}^{T} \tilde{Q}_s \Delta P_{s+1}$, and the profit per market transaction follows as

$$\Pi = \frac{1}{T} \sum_{s=1}^{T} \tilde{Q}_s \Delta P_{s+1}. \tag{1}$$

The inventory management of a trader will in general comprise short-run and long-run inventory cycles. Accordingly, profit might come from covariance based on either short-run or long-run comovements of inventory and price change. Given a data span limited to T observations, long-run comovement over T/N periods can be observed only N times, and their measurement involves higher standard errors as T/N becomes large. On the other hand, information asymmetries might have their most pronounced profit impact in the long run and thus appear only in the low-frequency comovements of inventory and price changes. This trade-off motivates a decomposition of profit in the frequency domain. Since the trading profit defined in equation (1) is a cross-product, basic spectral techniques may be applied directly. A Fourier analysis is used to extract the sinusoidal components of the inventory level and the price change at particular frequencies. If the inventory level and the price change are in phase (i.e., have peaks and troughs that match), then the contribution to the cross-product and the trading profit is positive; if they move out of phase, the contribution is negative.

[12] See Hansch, Naik, and Viswanathan (1998) for a similar approach. They also show that the initial inventory level Q_0 does not enter the term $\tilde{Q}_t = Q_t - \bar{Q}$.

A. Spectral Profit Decomposition

For the purpose of our study, it is not useful to report the profit contribution of each single frequency. Instead, we group frequencies into three frequency bands.[13] These are the high-frequency band, representing intraday profit; the medium-frequency band, corresponding to the intraweek profit; and the low-frequency band, measuring the profit contribution of weekly to quarterly inventory cycles. The spectral decomposition thus produces (frequency domain) profit subsamples. These subsamples are of different sensitivity to the microstructure of the market and the trading characteristics of a trader. High-frequency trading profit, for example, should be most sensitive to limited market depth or the bid-ask spread, whereas medium- and low-frequency profits are not.

Formally, the cross-product of equation (1) can be decomposed into its different spectral components represented by a function $\mathrm{Co}_{Q\Delta P}(\omega_k)$ known as the cospectrum.[14] The Appendix provides more details on technical aspects of the spectral decomposition. Let L,M,H denote a partition of the (positive) Fourier frequencies $\{\omega_1,\ldots,\omega_N\}$ into a subset L of low frequencies, a subset M of medium frequencies, and a subset H of high frequencies. We can then decompose profit into three elements:

$$\begin{aligned}\Pi &= 2\sum_{k=1}^{N}\mathrm{Co}_{Q\Delta P}(\omega_k)\\ &= 2\sum_{k\in L}\mathrm{Co}_{Q\Delta P}(\omega_k) + 2\sum_{k\in M}\mathrm{Co}_{Q\Delta P}(\omega_k) + 2\sum_{k\in H}\mathrm{Co}_{Q\Delta P}(\omega_k) \\ &= \Pi^L + \Pi^M + \Pi^H.\end{aligned} \tag{2}$$

Because profit is given by the cross-product of the inventory level and price change, scaling the inventory cycle also scales the trading profit by the same factor. To obtain a standardized profit measure across stocks and different inventory cycles, we normalize profit with the standard deviation of the inventory value $V_s = \tilde{Q}_s P_s$ in the respective frequency bands. The variance of the inventory value can also be decomposed into the corresponding frequency bands as

$$\mathrm{Var}(V) = \mathrm{Var}(V^L) + \mathrm{Var}(V^M) + \mathrm{Var}(V^H). \tag{3}$$

[13] This approach is suggested by Engle (1974, 1978).

[14] A technical condition for the spectral decomposition is stationarity of the price changes and the inventory process. Price changes are stationary, and financial institutions typically impose trading limits on the proprietary positions of traders. We do not formally test for stationary inventories because of the short data span of only four months and the notoriously low power of such tests.

The standard deviations of the three variance components represent the inventory risk measure; that is, $\mathrm{RISK}^f = \sqrt{\mathrm{Var}(V^f)}$. Standardized profits for the three frequency bands $f = L,M,H$ are defined as

$$\widetilde{\Pi}^f = \frac{\Pi^f}{\sqrt{\mathrm{Var}(V^f)}}. \tag{4}$$

In order to allow for a simple interpretation of standardized profits, we scale the measure RISK^f to have a unit mean across all traders in the same stock. The term $\widetilde{\Pi}^f$ therefore expresses the profits of a trader with the average (representative) inventory risk in the respective stock and frequency band.

The profit calculation is based only on proprietary trades, so an important measurement issue is the correct self-identification of the trade type. For example, a trader may incorrectly declare client trades as proprietary trades; this implies an inventory measurement error $\tilde{Q}^m_s$.[15] As a consequence, profit would be mismeasured by $(1/T)\sum_{s=1}^{T}\tilde{Q}^m_s\,\Delta P_{s+1}$, which becomes zero (for a large T) if the inventory measurement error is uncorrelated with the price change ΔP_{s+1}. Thus, only a correlation of the inventory measurement error with the price change distorts the profit statistics.

B. Econometric Specification

We use a linear regression model to explain the standardized profit $\widetilde{\Pi}^f_{ij}$ of trader $i = 1,2,\ldots,N_I$ in stock $j = 1,2,\ldots,N_J$ as a linear function of the locational characteristics $\mathbf{X}_{ij}$ and behavioral characteristics $\mathbf{Y}_{ij}$ summarized in the matrix $\mathbf{Z}_{ij} = (\mathbf{X}_{ij}, \mathbf{Y}_{ij})$. The locational characteristics identify a subset of traders through dummy variables. This implies that we can allow only for random effects μ^f_i within the trader population. The stock-specific profitability, on the other hand, can be captured by a fixed effects α^f_j for each stock. The panel specification is of the form

$$\widetilde{\Pi}^f_{ij} = \alpha^f_j + \beta^f\mathbf{Z}_{ij} + \mu^f_i + \epsilon^f_{ij}, \tag{5}$$

where the errors μ^f_i and ϵ^f_{ij} are mean zero, uncorrelated with themselves and each other, uncorrelated with $\mathbf{Z}_{ij}$, and homoskedastic. The time series of the market-to-market profit (in transaction time) is calculated for each stock-specific profit account of each trader and separated into the profit contributions of the three frequency bands $f = L,M,H$. If there are N_j traders in stock j, then the total number of profit observations is $3 \times \sum_{j=1}^{N_J} N_j$.

[15] The self-declaration of the trades as client or proprietary trades is (to our knowledge) not subject to regular external controls by the market authorities, but it may be subject to internal controls. The scope of the internal controls is hard to evaluate. We emphasize that the trade type is not revealed in the open order book; strategic motivations for an incorrect declaration can therefore be discarded.

An important requirement for the profit decomposition is to preserve the comparability of the profit measures across traders. We therefore apply a uniform definition of the three frequency bands to all traders based not on a trader's individual transactions, but rather on all transactions in the market. This produces identical and comparable spectral frequency bands for all traders independent of the number of their transactions. The low-frequency band comprises the 10 lowest frequencies corresponding to inventory cycles of more than one week (intraquarter). The medium-frequency band is chosen to capture the profitability of intraweek cycles with the frequencies 11 to 100. The high-frequency band captures the intraday cycles with the remaining frequencies 101 to $T/2$.

Table II provides summary statistics for profit, standardized profit, and inventory risk. The average profit (standardized profit) per market transaction in the high-, medium-, and low-frequency bands are DM 0.04 (0.29), DM 0.12 (0.35), and DM 1.72 (1.44) per market transaction. The standard deviations are given by DM 3.25 (1.97), DM 7.22 (4.19), and DM 40.09 (15.64), respectively. Scaling the trading profit by the inventory risk (RISK) decreases the standard deviation of the profit distribution and reduces the role of profit outliers in our regression analysis. Our sample group of proprietary traders as a whole earned trading profits relative to other market participants. The high dispersion of profits and losses illustrates the considerable risk involved in proprietary trading. We also note that the standard deviation of the profit per transaction increases considerably as we consider the medium- and low-frequency bands, which corresponds to a similar increase in the average inventory risk in these frequency bands.

III. Determinants of Trading Profits

The dependent variables $\mathbf{Z}_{ij} = (\mathbf{X}_{ij}, \mathbf{Y}_{ij})$ require a detailed discussion. We distinguish exogenous locational characteristics $\mathbf{X}_{ij}$ for each trader as well as behavioral variables $\mathbf{Y}_{ij}$ that control for heterogeneity of trading behavior across the trader population.

A. Locational Trader Characteristics

The locational characteristics

$$\mathbf{X}_{ij} = (\text{FRANKFURT}_i, \text{FOREIGN}_i, \text{SWISS}_i, \text{PROXIMITY}_{ij}, \text{SIZE}_{ij}) \tag{6}$$

are chosen to reflect a potential information asymmetry across the trader population. Each variable corresponds to a test of one of the five hypotheses spelled out in the Introduction. The dummy variable FRANKFURT_i takes on the value of 1 for traders in Frankfurt and 0 otherwise; it measures the locational advantage for being in Germany's financial center and at the physical site of the stock market. The role of financial centers in information processing has been emphasized by Gehrig (1998). He argues that local

Table II

Summary Statistics

Locational dummy variables are introduced for traders in Frankfurt (FRANKFURT), for foreign traders in non-German-speaking locations (FOREIGN), for foreign traders in German-speaking locations of Austria and Switzerland (SWISS), and for traders located within a 100 km of the corporate headquarters (PROXIMITY) in case the corporation is headquartered outside Frankfurt. SIZE indicates the number of traders within the same institution trading the same stock. CLIENT indicates if a trader undertakes client trading parallel to his proprietary trading. INTENSITY gives the number of proprietary trades in the same stock. INITIATION indicates the percentage of initiated trades (market orders). Trading profits per market transaction, standardized profits per market transaction, and the standard deviation of the inventory value (RISK) are stated for the high-frequency(H),medium-frequency(M), and low-frequency (L) bands as well as for total profits in all frequency bands (T).

Variable	Minimum	Maximum	Mean	Std. Dev.
FRANKFURT	0	1	0.58	0.49
FOREIGN	0	1	0.06	0.23
SWISS	0	1	0.01	0.12
PROXIMITY	0	1	0.07	0.25
SIZE	1	48	11.8	12.3
CLIENT	0	1	0.15	0.36
INTENSITY	10	9,129	199	415
INITIATION	0	1	0.49	0.19
RISK (H) $\times 10^{-3}$	0.40	18,079	266	578
RISK (M) $\times 10^{-3}$	0.14	51,286	859	1,816
RISK (L) $\times 10^{-3}$	0.05	313,338	3,423	9,415
RISK (T) $\times 10^{-3}$	0.66	318,022	3,565	9,597
Profit (H)	−71.91	57.13	0.04	3.25
Profit (M)	−93.48	139.86	0.12	7.22
Profit (L)	−375.61	1,475.24	1.72	40.09
Profit (T)	−411.77	1,503.52	1.89	41.79
Stand. Profit (H)	−11.29	21.53	0.29	1.97
Stand. Profit (M)	−23.15	24.51	0.35	4.19
Stand. Profit (L)	−56.48	61.20	1.44	15.64
Stand. Profit (T)	−80.75	145.12	2.64	18.20

interaction between financial intermediaries in financial centers is crucial for the evaluation of equity (hypothesis H1).[16] A second consideration for including a Frankfurt dummy is the concentration of foreign bank subsidiaries and their traders in this city. If foreign bank subsidiaries do have an informational disadvantage relative to native institutions, then the Frankfurt dummy might capture this opposite effect. Unfortunately, our data do not allow us to distinguish foreign bank subsidiaries from German financial institutions. Table III shows the distribution of profit accounts by stock and

[16] See also Choi, Tschoegl, and Yu (1986), Choi, Park, and Tschoegl (1996), and Jaeger, Haegler, and Theiss (1992), who study the allocation of bank branches in different financial centers. According to their view, local branch representation presents an important information linkage.

Table III

Profit Accounts by Stock and Trader Location

Number of proprietary profit accounts with at least 10 transactions by stock and trader location. Distinguished are traders located in Frankfurt (FRANKFURT), foreign traders outside Germany in an non-German-speaking location (FOREIGN), foreign traders outside Germany in a German-speaking location of Austria and Switzerland (SWISS), and traders located within 100 km of the corporate headquarters of the stock company (PROXIMITY) in case it is different from Frankfurt. The proximity dummy is always set to zero for traders in Frankfurt to avoid any colinearity problem with the Frankfurt dummy.

		Trader by Location				
Stocks	Corporate Headquarters	FRANKFURT	FOREIGN	SWISS	PROXIMITY	All Accounts
ALV	Munich	215	22	5	32	374
BAY	Leverkusen	238	22	6	44	414
DBK	Frankfurt	274	32	8	0	499
DCX	Stuttgart	282	30	10	20	515
DTE	Bonn	244	24	5	33	405
LHA	Frankfurt	199	17	5	0	326
MEO	Cologne	197	18	3	36	326
MNN	Düsseldorf	233	19	6	40	395
RWE	Essen	188	15	2	24	285
SIE	Munich	236	32	7	36	428
VEB	Düsseldorf	209	22	5	36	359
Obs.		2,515	253	62	301	4,326

trader location. Frankfurt-based traders manage 58 percent of all profit accounts. Taking this high percentage of Frankfurt-based trading as evidence of the financial center hypothesis would be misleading. It might simply reflect the persistence of a geographic pattern that once required physical presence (on the floor), prior to the existence of a decentralized trading technology.

The variables FOREIGN_i and SWISS_i are dummies for two groups of traders located outside Germany. Foreign traders might face reduced access to the relevant information sources. This argument has been made by Kang and Stulz (1997) to justify the home equity bias. Brennan and Cao (1997) accept the same foreign-home information asymmetry to explain equity flow behavior. The dummy FOREIGN_i marks all trader locations where German is not an important or official language; it therefore captures cultural and linguistic information barriers and a geographic distance effect (hypothesis H2). The locations include Amsterdam, Copenhagen, London, Paris, and Vasa (Finland). This trader group accounts for 5.9 percent of the profit observations. The dummy variable SWISS_i includes the German-speaking locations in Austria and Switzerland (Lausanne, Linz, Vienna, Zug, Zurich). Only 62 profit observations (or 1.4 percent of all observations) concern a trader in this group. The dummy SWISS_i measures a pure geographic distance effect (hypothesis H3) under the assumption that a common language eliminates linguistic information barriers.

The fourth locational dummy variable, $\mathrm{PROXIMITY}_{ij}$, indicates a distance of less than 100 kilometers between the trader location and the headquarters of the company j for corporations located outside Frankfurt.[17] Proximity to the corporate headquarters might provide an advantage if information diffusion has a local geographic dimension and inside information of corporate headquarters is more important than information produced outside by financial intermediaries. This is hypothesis H4, the headquarters proximity hypothesis. The regional dispersion of the corporate headquarters helps us to distinguish it from hypothesis H1, the financial center hypothesis. Of the 11 stocks in our sample, 9 have corporate headquarters outside Frankfurt (see Table III). Altogether, 301 profit observations involve traders dealing from a corporate headquarters location other than Frankfurt.

The variable SIZE_{ij} measures the number of active traders in stock j who work for the same financial institution as trader i. This variable captures possible economies of scale in market making within a financial institution (hypothesis H5). A trader in a large bank with numerous other traders might have access to better information about either the fundamental value of the asset or the client order flow. Institutional size varies from 1 to 48 active traders within the same institution, with an average of 11.8 traders (see Table II). Foreign traders have on average fewer colleagues in the same institution who trade the same asset. This can be deduced from Table IV, which provides summary statistics for the different locational subsamples. A foreign trader in a non-German-speaking location has on average only 2.9 colleagues trading the same asset.

B. Behavioral Trader Characteristics

The behavioral trader characteristics

$$\mathbf{Y}_{ij} = (\mathrm{CLIENT}_{ij}, \mathrm{INTENSITY}_{ij}, \mathrm{INITIATION}_{ij}, \mathrm{RISK}_{ij}^{T}) \tag{7}$$

are our control variables. The dummy variable CLIENT_{ij} marks traders who do additional client trading parallel to their proprietary trading. Parallel client trading might create moral hazard problems for the trader. Kampovsky and Trautmann (1999) argue that front-running of client orders exists in the Xetra market. Hillion and Suominen (1998) find evidence that traders in the Paris stock market sacrifice proprietary trading profits in price manipulation in order to give clients the impression of better client account execution. We control for any effect of parallel client trading on proprietary trading profits by introducing a dummy. Approximately 15 percent of the trader population undertake parallel client trading. This percentage is higher (31 percent) for the subsample of Austrian and Swiss traders (see Table IV).

[17] Traders in proximity to Frankfurt headquarters (DBK, LHA) are not counted as proximity traders in order to avoid any colinearity problem with the Frankfurt dummy.

Table IV

Subsample Statistics

Summary statistics for the profit accounts of four distinct trader groups. We distinguish traders located in Frankfurt (FRANKFURT), foreign traders outside Germany in a non-German-speaking location (FOREIGN), traders outside Germany in a German-speaking location of Austria and Switzerland (SWISS), and traders located within 100 km of the corporate headquarters of the stock company (PROXIMITY) in case it is different from Frankfurt. The sample mean, median, and standard deviation are reported for the following variables: SIZE indicates the number of traders within the same institution trading the same stock; CLIENT is a dummy that marks a trader who undertakes client trading parallel to his proprietary trading; INTENSITY measures the number of proprietary trades in the same stock; INITIATION indicates the percentage of initiated trades (market orders); RISK (T) measures the standard deviation of the account value over all three frequency bands. We also report volume per trade, total profits, and standardized total profits.

	Traders by Location				
Variable	FRANKFURT	FOREIGN	SWISS	PROXIMITY	All Traders
SIZE					
Mean	14.4	2.9	2.2	8.3	11.8
Median	8.0	2.0	2.0	4.0	7.0
Std. Dev.	13.9	2.0	0.8	8.8	12.3
CLIENT					
Mean	0.09	0.13	0.31	0.18	0.15
Median	0.00	0.00	0.00	0.00	0.00
Std. Dev.	0.29	0.33	0.46	0.39	0.36
INTENSITY					
Mean	197	388	158	175	199
Median	76	183	51	43	66
Std. Dev.	404	529	222	392	415
INITIATION					
Mean	0.50	0.50	0.27	0.47	0.49
Median	0.50	0.50	0.24	0.47	0.49
Std. Dev.	0.19	0.16	0.25	0.20	0.20
RISK (T) $\times 10^{-3}$					
Mean	3,767	5,566	1,578	3,168	3,565
Median	1,420	2,204	341	669	1,138
Std. Dev.	8,048	11,251	4,448	18,600	9,597
Volume per Trade					
Mean	200	171	117	191	195
Median	183	157	88	170	177
Std. Dev.	103	90	98	98	102
Profit (T)					
Mean	0.08	−1.88	3.17	6.40	1.89
Median	0.51	−0.32	0.09	0.24	0.32
Std. Dev.	33.06	46.43	15.72	89.44	41.79
Stand. Profit (T)					
Mean	2.37	−3.32	2.74	3.82	2.64
Median	2.85	−2.17	3.22	3.44	2.89
Std. Dev.	18.09	18.48	17.83	18.23	18.20
Obs. per Trader	5.82	5.85	5.61	6.34	5.77
Obs.	2,515	253	62	302	4,326

The variable INTENSITY_{ij} denotes the number of trades undertaken by trader i in stock j over the sample period; it captures a potential linkage between market-making profit and trading intensity. A trader might specialize in trading a single stock (or a group of stocks) and thereby concentrate his trading profit in the respective account. Our trader sample shows considerable variation in trading intensity. The most active trader registered 9,129 trades compared to the average of 199. The number of trades per profit account averages 388 for the foreign traders in non-German-speaking locations and only 158 for the Austrian and Swiss traders. Traders with little transaction activity are less frequent in the subsample of traders in non-German-speaking locations; but their volume per trade does not exceed the average of the trader population.

The average trade direction is measured by INITIATION_{ij}, which indicates the percentage of transactions in stock j initiated by trader i. We refer to initiated trades as market orders. A high percentage of market orders implies a more active inventory management as opposed to a passive liquidity provision via bid-ask spread adjustment. The average trade initiation rate is 49 percent and its large standard deviation (19 percent) indicates considerable heterogeneity in trading behavior. The Swiss and Austrian traders stand out as liquidity providers, with a trade initiation rate of only 27 percent (see Table IV). However, this subsample is based on only 11 traders.

Although our profit measure is scaled by inventory risk, we include RISK_{ij}^{T} as an additional control variable. The justification is straightforward: given limited supply elasticity, large inventory cycles are likely to have a price impact. Therefore, trading profits cannot (ceteris paribus) increase linearly in trade size. The standardized profit measure neglects this nonlinearity. Including the variable RISK_{ij} controls for the profit loss due to limited market depth encountered by traders with large inventory cycles. Table IV shows that foreign traders in non-German-speaking locations manage profit accounts with a higher standard deviation for the account value.

The three variables SIZE_{ij}, INTENSITY_{ij}, and RISK_{ij}^{T} are characterized by loptokurtosis. This suggests that the logarithmic transformation given by $X_{ij}^{\nabla} = \log(X_{ij}/\overline{X}_j)$ relative to the sample mean $\overline{X}_j$ represents as a more suitable regressor. We also de-mean the trade initiation rate and denote it $\text{INITIATION}_{ij}^{\nabla}$. The intercept term α_j^f now has an economic interpretation. It states the average profit in stock j per market transaction of a representative proprietary trader located in Germany but outside Frankfurt and without proximity advantage.

IV. Estimation Results

In this section, we present the regression results. We use a GLS random effect estimator for unbalanced data (Baltagi (1995)). The profit equation (5) is estimated separately for the three frequency bands. Table V provides the parameter estimates for high-, medium-, and low-frequency profits; we also repeat the regression for total profits (over all frequency bands). These results do not require any frequency decomposition. The panel data could have a more complex error structure than assumed in our regression model, so we report ordinary standard errors (in parentheses) and the bootstrapped standard errors [in brackets].[18] Generally, bootstrapping yields standard errors that are not much different.

Each profit equation is estimated with and without the behavioral control variables. Including control variables increases the overall $\bar{R}^2$ from 0.021 to 0.142 (high-frequency band), 0.013 to 0.017 (medium-frequency band), and 0.011 to 0.014 (low-frequency band). The explanatory power of our independent variables is therefore quite modest. This should be expected if the return expectations of the traders have a low correlation with realized returns, irrespective of location. We start our discussion with the results on intraday trading.

A. Short-run Trading Profits

The baseline specification (Table V, column (1)) shows highly significant point estimates for the constant term and the PROXIMITY dummy. The constant term measures the average profit per market transaction in German marks (DM) for a German benchmark trader. A point estimate of 0.605 for a representative stock with approximately 30,000 quarterly market transactions implies a quarterly profit from intraday trading of DM 18,000 per profit account with at least 10 transactions. Not reported are the fixed effects, which capture excess profit in a particular stock (they are small and generally insignificant). The sum of the constant term and any stock-specific fixed effect is always positive. Proprietary intraday trading is therefore profitable for the representative trader in all 11 stocks.[19] The point estimate for the PROXIMITY dummy is 0.322 and is significant on a one percent level. This implies that geographic proximity to the corporate headquarters increases the quarterly trading profits from intraday trading in the respective stock by approximately DM 10,000. The negative coefficients for the FRANKFURT and FOREIGN dummies indicate a lower average profit for Frankfurt traders and foreign traders in non-German-speaking locations. However, their losses relative to the representative German benchmark trader are not statistically significant.

We augment the baseline specification to include behavioral controls (Table V, column (2)). The overall $\bar{R}^2$ increases substantially to 0.142. The point estimate for the foreign underperformance increases to -0.486 and is now statistically significant on a five percent level. It implies a quarterly relative loss from intraday trading of approximately DM 15,000 per account. A representative foreign trader who deals in 20 different stocks will take a relative quarterly loss of DM 300,000 from intraday trading alone. The proximity

[18] Bootstrapped standard errors were obtained from 1,000 draws of 756 traders with replacement.

[19] We employ the term profitability here in the sense of gross profitability of the proprietary trading activity only. Ignored are all costs that support the trading activity.

Table V

Determinants of Trading Profit

The proprietary trading profits of 756 traders in 11 German stocks in the Stoxx 50 index are pooled to obtain 4,326 individual profit accounts with at least 10 transactions each. A spectral decomposition is used to separate total profits of each account to intraday (high-frequency) profit, intraweek (medium-frequency) profit, and intraquarter (low-frequency) profit. We scale (standardize) profits by the standard deviation of the account value in the respective frequency band. Standardized trading profits are regressed on fixed effects for individual stocks (not reported) and locational dummies for various subsets of traders. We distinguish Frankfurt-based traders (FRANKFURT), foreign traders in non-German-speaking locations (FOREIGN), traders in the German-speaking locations of Switzerland and Austria (SWISS), and traders in local proximity to the respective corporate headquarters (PROXIMITY). The variable SIZE measures the number of traders in the same financial institution as the trader under consideration. The behavioral control variables are a dummy for parallel client trading (CLIENT), the trader's total number of trades in the respective stock (INTENSITY), the percentage of market orders among these trades (INITIATION), and a measure of the standard deviation of the inventory value in the respective stock (RISK). Variables marked with a $^{\nabla}$ are in logs and/or de-meaned. We use a GLS random effect estimator for unbalanced panels with random effects for each trader. Reported are ordinary standard errors (in parentheses) and bootstrapped standard errors [in brackets]. Significance on a five percent (*) or one percent level (**) is indicated.

	High-Freq. Profit		Medium-Freq. Profit		Low-Freq. Profit		Total Profit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.605**	0.601**	1.064**	1.136**	0.797	0.973	3.908**	4.341**
	(0.120)	(0.115)	(0.240)	(0.245)	(0.905)	(0.923)	(1.049)	(1.069)
	[0.107]	[0.108]	[0.218]	[0.219]	[0.795]	[0.840]	[0.889]	[0.917]
FRANKFURT	−0.169	−0.025	−0.402**	−0.400*	0.164	−0.067	−1.354	−1.076
	(0.112)	(0.100)	(0.154)	(0.160)	(0.614)	(0.634)	(0.732)	(0.749)
	[0.091]	[0.864]	[0.149]	[0.153]	[0.568]	[0.599]	[0.682]	[0.684]
FOREIGN	−0.292	−0.486*	−1.486**	−1.432**	−3.664**	−3.858**	−7.970**	−7.786**
	(0.232)	(0.202)	(0.305)	(0.309)	(1.230)	(1.240)	(1.472)	(1.471)
	[0.276]	[0.256]	[0.355]	[0.344]	[1.242]	[1.282]	[1.598]	[1.616]
SWISS	0.318	−0.142	−1.070	−1.298*	−1.433	−0.552	−2.602	−3.896
	(0.422)	(0.366)	(0.564)	(0.569)	(2.261)	(2.266)	(2.699)	(2.682)
	[0.306]	[0.300]	[0.491]	[0.533]	[1.162]	[1.213]	[1.673]	[1.702]

PROXIMITY	0.322**	0.312**	−0.183	−0.212	−1.595	−1.602	−0.474	−0.651
	(0.122)	(0.116)	(0.274)	(0.274)	(1.030)	(1.030)	(1.193)	(1.189)
	[0.133]	[0.121]	[0.231]	[0.231]	[0.937]	[0.930]	[1.114]	[1.090]
SIZE$^{\nabla}$	−0.118*	−0.017	−0.170**	−0.143*	−0.346	−0.351	−0.998**	−0.618*
	(0.047)	(0.041)	(0.064)	(0.066)	(0.256)	(0.261)	(0.305)	(0.309)
	[0.040]	[0.0358]	[0.067]	[0.070]	[0.234]	[0.251]	[0.291]	[0.296]
CLIENT		−0.060		−0.425*		−0.140		−1.112
		(0.107)		(0.189)		(0.744)		(0.875)
		[0.099]		[0.187]		[0.749]		[0.805]
INTENSITY$^{\nabla}$		0.567**		0.028		−0.090		1.320**
		(0.033)		(0.070)		(0.270)		(0.314)
		[0.053]		[0.087]		[0.289]		[0.364]
INITIATION$^{\nabla}$		−2.332**		−1.076**		4.307**		−2.225
		(0.160)		(0.330)		(1.270)		(1.480)
		[0.165]		[0.375]		[1.339]		[1.656]
RISK$^{\nabla}$		−0.387**		−0.082		0.125		−1.483**
		(0.029)		(0.060)		(0.232)		(0.270)
		[0.031]		[0.073]		[0.265]		[0.331]
Observations	4,326	4,326	4,326	4,326	4,326	4,326	4,326	4,326
Traders	756	756	756	756	756	756	756	756
$\bar{R}^2$ Within	0.015	0.088	0.005	0.008	0.009	0.012	0.010	0.014
$\bar{R}^2$ Between	0.033	0.256	0.020	0.021	0.022	0.029	0.032	0.047
$\bar{R}^2$ Overall	0.021	0.142	0.013	0.017	0.011	0.014	0.020	0.029
σ(Trader)	1.113	0.901	0.412	0.420	2.978	2.888	4.020	3.824
σ(Obs.)	1.610	1.547	3.986	3.983	14.928	14.907	17.050	17.023
σ(Total)	1.957	1.790	4.008	4.005	15.223	15.184	17.518	17.447

dummy is again significant at a one percent level. This indicates a role for geography if distance to corporate headquarters is very small. For the Swiss and Austrian traders, we do not find a statistically significant underperformance for intraday trading. We interpret this as evidence against the pure geographic distance hypothesis. The (negative) institutional size effect from the benchmark regression disappears if we introduce behavioral controls. High-frequency trading profits indicate no competitive advantage or disadvantage for traders in large financial institutions. Neither do intraday profits reveal any financial center advantage for traders located in Frankfurt.

Inspection of the point estimates of the behavioral control variables yields further insights. Parallel client trading is not significantly correlated with intraday profits. But the control variables for the number of trades (INTENSITY$^{\nabla}$), the average trade direction (INITIATION$^{\nabla}$), and the inventory risk (RISK$^{\nabla}$) are all highly significant, with t-values above 10. More frequent trading in a stock is positively correlated with the profitability of the respective account. A large number of trades might indicate trading specialization in a particular stock. The variable with the highest statistical significance level is INITIATION$^{\nabla}$. Traders relying on market orders in their inventory management have lower intraday profits, because trade initiation implies a short-run loss of the bid-ask spread. The coefficient on inventory risk (RISK$^{\nabla}$) is also negative. Higher inventory variation correlates with lower standardized profits. The control variable RISK$^{\nabla}$ captures trading costs due to limited market depth.

To check the robustness of our estimation results, we eliminate the one percent profit outliers. The same qualitative results are obtained. In particular, the underperformance of traders in non-German-speaking locations and the overperformance of proximity traders are both confirmed at similar significance levels for the reduced sample. The results were also robust with respect to the inclusion of volume (turnover) per trade or total volume as additional control variables.

Finally, we highlight the estimates for the error components. Including controls, the random effect for the trader has a standard deviation of σ(Trader) = 0.901, and the individual effect for each observation is σ(Obs.) = 1.547. Residual trading profits in different stocks are correlated if trading is undertaken by the same trader. However, the variance effect for individual stocks is much larger than the variance of the trader random effect. This suggests important diversification benefits for traders who spread their market-making activity over many stocks.

B. Medium- and Long-run Trading Profits

We now turn to the medium- and long-run trading profits, whose estimation results are reported in columns (3) and (4) and columns (5) and (6) of Table V. Highly significant for the medium-frequency profit are the constant term and the dummy coefficient for traders in non-German-speaking locations (FOREIGN). Intraweek proprietary trading is again profitable for the representative German trader, but it is, on average, loss-making for the foreign traders. The relative profit shortfall for traders in non-German-speaking locations is statistically significant, with a t-statistic of 4.9. Medium-frequency profits therefore show clearer evidence for foreign underperformance than is evident in high-frequency trading. The point estimate of -1.432 indicates that the average relative loss of foreign traders increases by a factor of 3 as we move from intraday profits to intraweek profits. We conclude that the information disadvantage of foreign traders has a larger impact on their intraweek trading than on their intraday trading results. For Austrian and Swiss traders (SWISS) we obtain a profit shortfall with a three percent significance level, but only if we include the behavioral control variables. This underperformance of the Austrian and Swiss traders is weak evidence for the pure geographic distance hypothesis. Institutional size shows a weak negative correlation with profitability even after inclusion of the control variables. There is no evidence for increasing institutional scale economies in proprietary trading. Neither do we find any support for the financial center hypothesis; the data indicate, in fact, a moderate underperformance of traders located in Frankfurt.[20]

For the low-frequency profit, the constant term is again positive but is not statistically significant. The low sampling rate for low-frequency covariances generates noisy profit statistics, as evidenced by the large error component estimates: The estimated overall standard deviation of the residual errors is seven times higher than for the high-frequency profit. Nevertheless, the point estimate for traders in non-German-speaking locations (FOREIGN) is negative at a one percent significance level under both inclusion and exclusion of the control variables. All other locational characteristics show no statistically significant correlation with low-frequency profit. In particular, the headquarters proximity dummy is insignificant for both intraweek and intraquarter profits. Hence, local proximity seems to provide only very short-lived information advantages. One example of such an advantage might be insider information received immediately prior to a public announcement.

The coefficient estimates for the control variables provide additional insights. The number of trades ($\text{INTENSITY}^{\nabla}$) is uncorrelated with medium- and low-frequency profits. Similarly, the coefficient for the inventory risk variable (RISK^{∇}) is insignificant for medium- and low-frequency profits. This is intuitive because longer inventory cycles will moderate losses on the bid-ask spread, since market depth is larger in the long run. Finally, the trade initiation rate ($\text{INITIATION}^{\nabla}$) is negatively correlated with high- and medium-frequency profits but positively correlated with low-frequency profits. This implies that traders relying on market orders recover some of

[20] One explanation for this result is the strong representation of foreign banks' branches in Frankfurt. They might have an informational disadvantage relative to native institutions and bias the Frankfurt coefficient downward. Unfortunately, our data do not allow further disaggregation of Frankfurt-based traders.

their high- and medium-frequency losses by low-frequency profits. The evidence reveals a market microstructure in which traders with better information submit market orders. These traders lose on the spread in the short run, but they gain in the long run.

To measure overall performance of the trader types, we also look at the regression for total profit provided in columns (7) and (8) of Table V. The point estimates for the constant term and the FOREIGN dummy are again highly significant. Total foreign underperformance (over all three frequency bands) amounts to almost DM 8 per market transaction. For a stock with 30,000 quarterly transactions, we obtain a quarterly relative proprietary trading loss of approximately DM 240,000 per account. This is a surprisingly high locational disadvantage for foreign-based traders. We can only speculate on the exact source of the information disadvantage for the foreign trader community. The major commercial information networks, such as Reuters and Bloomberg, transmit messages in both German and English. Multilingual networks should therefore tend to eliminate information asymmetry. Instead, some traders cite oral communication networks; others mention private newsletters circulating among traders. More comprehensive microdata on individual traders are needed to distinguish between different explanations.

V. Conclusions

We have examined the proprietary trading profits of 756 traders located in eight European countries with equal access to the electronic trading system Xetra of the German Security Exchange. We examined their trading profits on the 11 German blue-chip stocks in the Stoxx 50 index and undertook a spectral profit decomposition into intraday, intraweek, and intraquarter profits. The results can be summarized as follows.

1. Traders located in the financial center (Frankfurt) do not outperform traders in other German locations. This suggests that local interaction between traders is not crucial to trading performance.
2. Traders in non-German-speaking locations show a statistically significant underperformance for intraday, intraweek, and intraquarter trading profits. Their total underperformance is economically large and averages approximately DM 8 per market transaction and stock for all proprietary profit accounts with at least 10 trades in the four-month sample period. This implies an average quarterly underperformance of approximately DM 240,000 per actively traded blue-chip stock. Most of this average underperformance can be attributed to the lower trading frequencies and is therefore extremely hard to detect, given the large overall dispersion of individual trading profits and the small number of trader observations within any financial institution.

3. We find some evidence for an underperformance of Austrian and Swiss traders in medium-frequency (intraweek) trading. Overall, the evidence for their underperformance is weak. But this might be explained by a lack of statistical power, given the small number of Austrian and Swiss traders. Hence, we hesitate to discard the pure geographic distance hypothesis in favor of exclusively linguistic and cultural information barriers.
4. Traders located near corporate headquarters of the traded company outperform other traders in high-frequency trading of the respective stock. Medium- and low-frequency trading shows no effect of local proximity on trading profits. A plausible explanation is that local traders find it easier to establish and maintain a privileged relationship with a company insider who might communicate information shortly before it becomes public. However, this proximity advantage is quantitatively small and restricted (by definition) to the subset of stocks with local headquarters.
5. We find weak evidence for decreasing economies of scale on the institutional level if size is measured by the number of traders actively trading for the same financial institution. We exclude increasing informational scale economies in proprietary trading. In other words, large financial institutions do not have more profitable proprietary traders.

Of these results, the most important contribution of our paper is evidence of large profit differences for the proprietary trading of domestic versus foreign traders in non-German-speaking locations. This result is obtained for all three spectral dimensions and is robust to various controls for behavioral trader heterogeneity. The presented evidence concerns information asymmetry among professional traders dealing in very large and liquid blue-chip stocks. The revealed information asymmetry is likely to present only a lower bound on similar effects for smaller stocks. Using more comprehensive data to explore this information asymmetry and its source is a worthwhile task for future research.

Appendix: Spectral Decomposition

Here we provide a brief technical overview of the spectral decomposition for the profit time series into high-, medium-, and low-frequency profits. Let X_t and Y_t represent two time series of length T and assume that X_t has a zero mean. We develop the case in which T is an odd integer and define positive Fourier frequencies $\omega_k = 2\pi k/T$ for $k = 1, \ldots, N$ and $N = (T-1)/2$. The Fourier transform of X_t is given by

$$J_x(\omega_k) = \frac{1}{T} \sum_{t=1}^{T} X_t e^{-i\omega_k t},$$

where $i = \sqrt{-1}$ and $J_x(\omega_k)$ represents Fourier components of the series X_t at frequency ω_k. Furthermore, we define coefficients α_k^x and β_k^x for the series X_t as

$$\alpha_k^x = \frac{1}{T}\sum_{t=1}^{T} X_t \cos(\omega_k t) \quad \text{and} \quad \beta_k^x = \frac{1}{T}\sum_{t=1}^{T} X_t \sin(\omega_k t)$$

to express the Fourier components as $J_x(\omega_k) = \alpha_k^x - i\beta_k^x$. Similarly, we obtain the Fourier components of Y_t as $J_y(\omega_k) = \alpha_k^y - i\beta_k^y$. We can recover the time-series representation by using the inverse transform

$$X_t = 2\sum_{k=1}^{N} \alpha_k^x \cos(\omega_k t) + \beta_k^x \sin(\omega_k t),$$

which expresses each data point in terms of the N frequency components. The cross-product of X_t and Y_t can be restated as

$$\Pi = \frac{1}{T}\sum_{t=1}^{T} X_t Y_t = 2\sum_{k=1}^{N} (\alpha_k^x \alpha_k^y + \beta_k^x \beta_k^y) = 2\sum_{k=1}^{N} J_x(\omega_k)\overline{J_y(\omega_k)},$$

where the overbar denotes the complex conjugation (see Hamilton 1994, p. 272). This equivalent representation reveals the contribution of the various frequency components to the cross-product. These frequency components are the sample equivalent of the cospectrum at frequency ω_k,

$$\mathrm{Co}_{XY}(\omega_k) = J_x(\omega_k)\overline{J_y(\omega_k)}.$$

We can now partition the set of frequencies $\{\omega_1, \ldots, \omega_N\}$ into different frequency bands and so capture their respective contribution to the cross-product. For a partition into a low-frequency band L, a medium-frequency band M, and a high-frequency band H, we obtain the decomposition

$$\Pi = 2\sum_{k\in L} \mathrm{Co}_{XY}(\omega_k) + 2\sum_{k\in M} \mathrm{Co}_{XY}(\omega_k) + 2\sum_{k\in H} \mathrm{Co}_{XY}(\omega_k) = \Pi^L + \Pi^M + \Pi^H.$$

The market-to-market profit definition of equation (1) has a cross-product with one lagged variable. Shifting the original sequence for the price change by one observation allows a simple computation.

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